Zero-shot classification of ECG signals using a CLIP-based model

Navmeet S. Jassal, Konstantin Egorov\*, Semen BUDENNYY,2

1Laboratory X, Institute X, Department X, Organization X, City X, State XX (only USA, Canada and Australia), Country

2Laboratory X, Institute X, Department X, Organization X, City X, State XX (only USA, Canada and Australia), Country

**\* Correspondence:**Corresponding Author  
ndzhassal2@edu.hse.ru

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Abstract

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# Introduction

According to the World Heart Federation (WHF), a leader in global cardiovascular health, among other reports from leading clinicians, researchers and institutions, cardiovascular diseases (CVDs) are a leading cause of mortality worldwide [17; 22; 25; 36]. In the United States, the Center for Disease Control (CDC) estimates that the annual total cost associated with CVD-related treatment and death is approximately $219 billion dollars (USD) per year [18; 21]. Given the financial and socioeconomic burdens of CVDs, it is essential that individuals receive timely and accurate medical care for the diagnosis, treatment, and ongoing care of CVDs.

An electrocardiogram (ECG) remains the medical standard and benchmark for the identification and diagnosis of CVDs with more than 300 million ECGs being performed globally [7]. In general, ECGs measure the changes in electrical membrane potential of the heart across different directions of the body and are often referred to as leads with a 12-lead ECG report being the most common type of report [14; 29].

# Related Works

# Materials and Methodology

# Results

# Discussion

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